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► To cite this version:

Lefebvre Antoine, Nicolas Courty, Thomas Corpetti. Monitoring urban transformation in the old foreign concessions of Shanghai from 1987 to 2012. ISRSE35 - International Symposium on Remote Sensing for Environment - Earth observation and Global Environmental Change, Apr 2013, Beijing, China. pp.1–7. hal-00861694

HAL Id: hal-00861694

<https://hal.science/hal-00861694>

Submitted on 13 Sep 2013

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Monitoring urban transformation in the old foreign concessions of Shanghai from 1987 to 2012

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Abstract. This paper is concerned with morphological change analysis in the old foreign concessions of Shanghai from 1969 to 2010. To that end, we use a series of 17 Landsat TM and Landsat ETM + images on which we estimate some feature parameters. The analysis of the resulting time series enables to isolate changes from traditional constructions to new buildings or gardens. Our results show that 70 % of the old urban pattern was converted in modern high-rise buildings and green spaces.

1. Introduction

Along with the beginning of Deng Xiaoping reforms in 1978 and the opening to a market economy, China was dealt with a 'real estate boom' in the 1990's [1]. At the same time, historical cities have been exposed to important urban transformations. Located in the centre of urban activities, they constitute a prime area for the development offices and high standard housing. As a consequence, real estate lobbies for a rapid renewal of the old city [2]. The historical Chinese cities — and more generally Asian ones — tend to be reshaped as urban skylines composed of high-rise buildings at the expense of architectural heritage conservation while in the same time, some "green" plan have promoted the creation of new green spaces. Therefore, we assist to a transformation of traditional construction either into gardens or to new and modern buildings. Monitoring this demolition of the urban heritage is hence of great interest in order to have a better understanding of the city's evolution.

In this paper, we suggest to exploit time series of remote sensing data to classify the observed changes (no changes, changes from traditional construction to new buildings or to gardens). The paper is organized as follows: in section 2 we present the study area and available data. Section 3 introduces the classification methodology and section 4 shows our experimental results.

2. Study area and Data

2.1. Shanghai old foreign concession

This study focuses on the Shanghai old foreign concession. In the middle of the 19th century, foreign concessions built numerous housing that mix Chinese and foreign styles of architecture. Narrow streets and small terraced houses, named *shikumens* (石库门), characterize this particular well known

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urban pattern as *lilongs* (里弄). Over the past 15-20 years, modern high-rise buildings have replaced most of them and remaining ones have been preserved. This phenomenon reflects the emerging land and real estate market in the 90's, which led Shanghai to deal with urban development and preservation.

2.2. Satellite images

The study concerns a temporal period of 25 years (from 1987 to 2012) where a series of 17 images is available. They are issued from the Landsat 4 TM and Landsat 7 ETM + sensors. They provide data in 7 distinct channels including visible colour, infrared, mid-infrared, thermal infrared. The spatial resolution is 30 m and Landsat 7 ETM + has a panchromatic channel with a 15 m resolution. All details are given in table 1.

Table 1. List of images composing SITS

#	Date	Sensor
1	1987-05-18	Landsat TM
2	1993-06-03	Landsat TM
3	1995-11-16	Landsat TM
4	2000	Landsat 7 ETM +
5	2001	Landsat 7 ETM +
6	2003-07-27	Landsat 7 ETM +
7	2003-09-27	Landsat 7 ETM +
8	2005	Landsat 7 ETM +
9	2006-08-02	Landsat 7 ETM +
10	2007-03-30	Landsat 7 ETM +
11	2007-05-17	Landsat 7 ETM +
12	2008-07-06	Landsat 7 ETM +
13	2010-04-07	Landsat 7 ETM +
14	2010-05-25	Landsat 7 ETM +
15	2011-04-26	Landsat 7 ETM +
16	2011-09-01	Landsat 7 ETM +
17	2012-04-28	Landsat 7 ETM +

2.3. Per-parcel segmentation

In this study, instead of classifying each pixels independently (as we did in [3]), we prefer to rely at an object level where each one, also named “block” in this paper, corresponds to a structural entity (group of buildings, green spaces). To that end the primary roads are used to segment the urban pattern in blocks of building. Most of urban changes in Shanghai mainly affect an entire block of building and as a consequence, the “building block” is defined as the smallest element of study. In practice we used the Open Street Map (OSM) road networks to delineate these buildings blocks. OSM is a collaborative project to create and provide free GIS data. OSM road network in Shanghai is up-to-date and well completed; it includes the primary network and some secondary alleys. It, then, constitutes a suitable vector data to perform a per-parcel classification.

Let us now turn to the presentation of the method.

3. Methodology

The proposed approach is composed of two steps: 1) Spectral feature computation for each block independently in all images; 2) Denoising each temporal profile of feature associated with each pixel and 3) Classification of the time series. These three steps are detailed below.

3.1. Spectral feature computation for each block in each image

Several possibilities exist to characterize the spectral information in each block (first or second order statistics). Here we use the simplest one that is the mean reflectance in each spectral band.

3.2. Denoising of temporal profiles

We assume that the construction of a building is fast and induces a perennial land-use. Consequently, urban change can be modeled as an abrupt and irreversible evolution in multi-temporal feature parameters. As for the evolution from traditional housing to gardens, this can be represented with a jump of feature in infrared thermal and thermal infrared bands whereas the panchromatic ones decreases. The various temporal profiles associated with their corresponding changes are depicted in figure 3.

However classifying the temporal profiles directly issued from the raw data is not the optimal solution. In practice, the series are indeed inhomogeneous because of the noise, the different nature of input images (two different sensors) that introduce variability in the features and due to the different conditions of acquisition (illumination, climatic conditions...). This yields some noise in the series, as illustrated in figure 1.

Therefore, instead of dealing directly with time series issued from images, we rather prefer to fit a threshold function using maximum likelihood identification. This relies on the assumption that only one kind of change appears during the concerned period, which is quite reasonable. Three parameters are extracted to characterize the threshold function: first and second value and time of change. These parameters are the ones required to highlight the various changes. Examples of fitted functions are also visible in figure 1.

3.3. Classification of the time series

Let us recall here that 3 thematic classes are expected:

- 1) Change from old urban pattern to building;
- 2) Change from new urban pattern to parks and gardens;
- 3) No Change.

In practice, we rely on a Support Vector Machine (SVM) algorithm [4]. The main idea consists in performing the discrimination between classes in a transformed domain where the separation is clearer. One of the main idea consists in using a so-called *kernel* function: instead of defining the complete mapping function to Φ perform the transformation, only the scalar product $\langle \Phi(x), \Phi(y) \rangle$ (i.e. the kernel), that enables a comparison between the data in the mapped space, has to be known. The comparisons of the training set are defined through the kernel functions and the best separation, i.e. the largest gap between the classes, is used as a linear discriminator. New examples to classify are then compared into the mapped space and depending on their position with respect to the frontier, a label is assigned. Concerning the kernel, we use a Gaussian one to compare vectors of threshold parameters between classes.

A training dataset is defined by photointerpretation of the Landsat images and the very high-resolution images available on Google Earth. Samples selection and model calibration are then performed at the latest acquisition date. The model is then applied retrospectively to the other images.

Let us now introduce our results.

4. Results

The methodology presented in the previous section has been tested on the series of 17 images over the period 1987-2012. In order to validate our methodology, we have first divided the training set, composed of 40 profiles for each class, in two sub-sets: the first one is composed of 20 series for each class that are used to train the algorithm and the second sub-set, composed of 20 series, is used for validation. Our results exhibit an overall kappa of 0.78, which is quite satisfactory given that the data are mainly corrupted with noise. When applying this process to the overall image, one can observe that many green areas have been kept during the evaluation period. As for build structures, 70% of them have been destroyed in order to create modern buildings (87%) or to create green spaces (13%). These classification results can be seen in figure 2. These results are quite in accordance with our knowledge on Shanghai's evolution. Considering that the study of area was made of an old urban pattern, we notice the considerable transformation of the old city. Firstly, the transformation occurred around People's Square on Nanjinglu (which is the most famous shopping street in Shanghai) and also along Huaihai Road. Nanjinglu and Huaihai Road are then mainly composed of shopping malls and business centers. At the North of Huaihai Road, a major change was also the creation Yanzhong greenbelt in 2003.

The former walled city has been affected as well. Divided by two main traffic arteries, high-rise buildings appeared in its center at the beginning of the 2000's.

5. Conclusion

In this article, we have proposed a methodology able to monitor the structural changes that have appeared in the old foreign concessions of Shanghai during the period 1987-2012 from a set of Landsat images. It is based on a delineation of the structural elements through the road delineation issued from OSM. In a second step, some basic features (namely the mean radiance) in each band and each block of the data are computed. To simplify the resulting series of features, we have fitted to each of them a threshold function able to properly isolate the changes. Finally, the changes are classified using a SVM technique on the threshold functions. Results brings out 70% of the study area has been demolished in order to create modern buildings (87%) or to create green spaces (13%).

6. References

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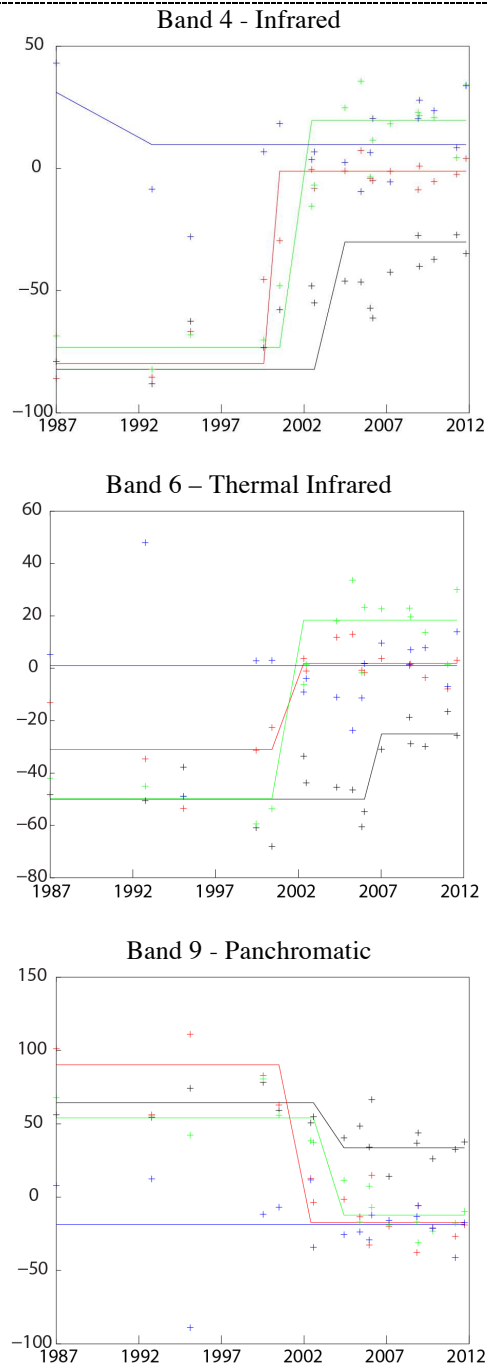


Figure 1. Change detection profile.

Black line: old urban pattern (No change)

Blue line: Green spaces (No change)

Red line: transition from old urban pattern to high-rise building

Green line: transition from old urban pattern to green spaces

